CAHIER D'ÉTUDES
WORKING PAPER

N° 31

A MONTHLY INDICATOR OF ECONOMIC ACTIVITY FOR LUXEMBOURG

Muriel Nguiffo-Boyom

March 2008

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME
1998 - 2008
10 ANS

A Monthly Indicator of Economic Activity for Luxembourg

Muriel Nguiffo-Boyom*†
Banque centrale du Luxembourg

March, 2008

Abstract

This paper presents a new indicator of economic activity for Luxembourg, developed using a large database of 99 economic and financial time series. The methodology used corresponds to the generalised dynamic-factor models that has been introduced in the literature by Forni *et alii* (2005), and the model as been estimated over the period from June 1995 to June 2007. Several means have been used to evaluate its forecasting performances and results are satisfactory. They in particular give clear evidence that our indicator allows to obtain better forecasts of the GDP growth relative to a more classical approach that relies on GDP past values only. This indicator is calculated on an experimental basis and changes may be integrated.

*Banque centrale du Luxembourg; e-mail: muriel.nguiffo-boyom@bcl.lu

†The author thanks the joint team on short-term forecasting of the ESCB Working Groups on Econometric Modelling and on Forecasting for sharing their Matlab code. I am also grateful for comments received after presentations at the Banque centrale du Luxembourg and at the Banque Nationale de Belgique. The views expressed in this paper are personal and do not necessarily reflect those of the Banque centrale du Luxembourg.

Résumé non-technique

L'indicateur synthétique d'activité de la BCL pour l'économie luxembourgeoise repose sur le modèle à facteurs dynamiques généralisé, introduit par Forni, Hallin, Lippi et Reichlin (2005). Cette approche permet de résumer, à des fins d'analyses conjoncturelles, l'information contenue dans un vaste ensemble de séries économiques et financières. En effet, le modèle à facteurs dynamiques généralisé postule l'existence d'un nombre réduit de facteurs qui sont à l'origine des variations de chacune des séries individuelles de l'échantillon. Ces facteurs, qui peuvent être vus comme des chocs fondamentaux qui influencent l'ensemble de l'économie expliquent une partie non-négligeable des évolutions de chaque série.

Cette méthodologie des modèles à facteurs dynamiques généralisé est appliquée à un échantillon composé de 99 séries. Il s'agit d'une part du PIB trimestriel - qui est mensualisé par interpolation linéaire - et, d'autre part, de 98 séries mensuelles. Ces dernières couvrent un champ relativement large puisque l'échantillon est composé d'indices de prix, de séries financières, de soldes d'opinion issus d'enquêtes de conjoncture, d'indices de la production industrielle, de chiffres d'affaires, de statistiques relatives à l'emploi et au commerce extérieur. Les résultats obtenus montrent que trois facteurs permettent d'expliquer plus de 60% de la variance totale de l'échantillon et, in fine, de construire l'indicateur d'activité.

Par construction, cet indicateur d'activité fluctue autour de zéro. Lorsqu'il évolue au-dessus (en-dessous) de zéro, l'activité croît à un rythme supérieur (inférieur) à sa moyenne historique - qui équivaut à un taux de croissance trimestriel du PIB de +1,1% environ. Lorsqu'au contraire il se situe à un niveau proche de zéro, l'activité croît à un rythme proche de sa moyenne historique. L'indicateur a fait l'objet de plusieurs évaluations. Dans un premier temps, ses propriétés explicatives et prédictives ont été explorées. Pour ce faire, plusieurs régressions reliant le taux de croissance du PIB publié par le STATEC à l'indicateur d'activité ont été considérées. Ces équations ont été estimées sur la période allant du second trimestre 1995 au second trimestre 2007. Les résultats d'estimations des équations font apparaître que rétrospectivement, les mouvements de l'indicateur d'activité permettent d'anticiper ceux du PIB de manière relativement satisfaisante.

Dans un second temps, les sources potentielles de révisions de l'indicateur ont été étudiées et quantifiées. La première vient de la prise en compte de nouvelles données. Dans notre cas, la fréquence mensuelle de publica-

tion des séries implique que chaque mois, 98 observations supplémentaires par rapport à la période précédente sont prises en compte pour la construction de l'indicateur. La seconde est due au traitement statistique des séries de l'échantillon. Il s'agit principalement des corrections des variations saisonnières et des points aberrants qui, effectuées mensuellement, entraînent des variations dans l'historique des séries. La dernière source de révisions restrospectives est liée à la publication des comptes trimestriels, qui s'accompagnent de révisions du PIB. Les simulations qui ont été effectuées montrent que toutes choses égales par ailleurs, la prise en compte de 98 nouvelles observations implique des révisions des valeurs présente et passées de l'indicateur. En moyenne, l'ampleur de la révision mensuelle est modeste. Les 12 derniers points sont cependant relativement plus révisés au mois le mois, avec une amplitude moyenne proche de 0,10 point. Le traitement statistique des séries mensuelles, pour sa part, ne semble pas être un facteur additif contribuant aux révisions de l'indicateur. Les révisions du PIB, en revanche, expliquent en grande partie celles de l'indicateur d'activité. Ainsi, entre les deux dernières publications des comptes trimestriels, l'ampleur de la révision moyenne de l'indicateur a été de l'ordre de 0,30 point. Ce dernier chiffre mérite néanmoins d'être relativisé, puisqu'il tombe à 0,15 point lorsque l'ensemble des révisions des comptes trimestriels sont prises en compte.

Au final, l'indicateur synthétique d'activité de la BCL pour l'économie luxembourgeoise est le reflet des évolutions à moyen-terme de l'activité. Il fournit une information mensuelle sur les performances relatives de l'économie du Grand-duché. Si les simulations ont montré que l'indicateur d'activité est sujet à révisions, il n'en reste pas moins que l'ampleur de celles-ci reste modérée. A ce stade, l'indicateur est calculé sur base expérimentale, pouvant donc faire l'objet de modifications méthodologiques.

1 Introduction

A major aim of an economist is to track the economic development and to provide a diagnostic on the present economic situation. The assessment of the general economic situation should also play a major role in the decision-making process of every rationale economic agents (consumer and producer), whose function is to maximise either its profit or well-being intertemporally. As part of both economic and monetary authorities, this assessment is primordial since spillover effects of a political decision aims to be optimal. Both inadequately and untimely policy may indeed have adverse effects on the economy. This is why nowcasting plays a central role in policies decision-making.

Nowcasting requires to focus on times series data that can provide information on the current state of the economy. On the one hand, Gross Domestic Production (GDP) is frequently considered as the reference series. By construction, it is a reflect of the way the businesses of a country function. It has nevertheless several drawbacks: it is released on a quarterly frequency, with a certain delay and may be subject to significant revisions afterwards. On the other hand, there exist numerous economic and financial time series with shorter publication delays and other notable advantages such as fluctuations in line with those of GDP, monthly-frequency release or high quality of data. This is mostly the case for monthly statistics related to employment, industrial production, interest rates or business surveys, which are published by national statistics institutes or central banks. At this stage, two main approaches exist. The first one requires to focus on a limited number of series. It consists in selecting a reduced number of series and tracking their development. The selection criteria may be based on the ex-post ability of the series to reproduce the reference series movements; or on a priori beliefs based on economic theory. Given the huge quantity of time series, the choice may almost be judged as subjective. In every case, the series may be either individually tracked or aggregated in a synthetic index whose changes will be tracked. This is the strategy that has been adopted by The Conference Board and the OECD for instance. The second approach stimulates the use of a large number of series. It indeed assumes that a better representation of the economic development should be obtained by considering a large dataset. In that case, the objective is more how to summarizes the information contained in a large sample of economic and financial time series than how to select individual series. This latter approach has led to the development of a vast literature, in which more and more sophisticated dynamic factor models have emerged since the first ones proposed by Geweke (1977) and Sargent and Sims (1977). In its basic version, the dynamic factor model assumes that a vector of N times series may be decomposed into two unobservable orthogonal components: a common component and a idiosyncratic component. The dynamic of each of the N common component is driven by a small number of factors, smaller than N, while the N idiosyncratic components are driven by N two-to-two uncorrelated idiosyncratic shocks. Since then, several extensions have been introduced to the dynamic factor model version of Geweke (1977) and Sargent and Sims (1977). Diebold and Rudebusch (1996) and Kim and Nelson (1998) allow the parameter of the dynamic factors to change over the business cycle. In the non-parametric models of Stock and Watson (2002a and 2002b) and Forni *et alii* (2000 and 2005) for instance, the number N of series may be extremely large and the idiosyncratic components are allowed to be weakly cross-correlated. More recently, Doz *et alii* (2005) have implemented a parametric version of a dynamic factor model that also allows the number N to be extremely large. These successive refinements introduced in factor models have come with an increasing empirical forecasting literature dealing with factor models. Central banks have particularly shown an interest in using dynamic factor models, mostly to generate GDP or inflation forecasting. A non-exhaustive list encompasses Schneider and Spitzer (2004) that deal with Austrian GDP forecasting, both Schumacher (2005) and Schumacher and Breitung (2006) with German GDP forecasting, den Reijer with Dutch GDP forecasting and Van Nieuwenhuyze (2004) with Belgium GDP forecasting. Moreover, the European System of Central Banks WGEM/WGEF[1] Short-Term Forecasting Team (SFTC) has deeply focused on factor models as discussed in Ruenstler *et alii* (2007). As for inflation forecasting we can cite the work of Bruneau *et alii* (2003) for France, and those of Cristadoro *et alii* (2005) and Giannone and Matheson (2007) who construct a core inflation indicator respectively for the euro area and New Zealand.

In the present paper, we use the model of Forni *et alii* (2005) to construct a monthly indicator of economic activity for Luxembourg. Our dataset is made up of 98 monthly series plus a quarterly one, the GDP of Luxembourg that has been linearly interpolated to obtain a monthly series. We find three dynamic factors to explain a large part of the total variance of our dataset. The combination of these factors also permit to extract the common component of the monthly GDP, which is our raw indicator of economic activity for Luxembourg. We obtain the smoothed indicator (indicator thereafter) by removing from the raw indicator the most volatile movements having a propensity to be inverted in the short-run. Our approach is quite similar to the one used by Altissimo *et alii* (2001) for both the construction and the

[1]For Working Group on Econometric Modelling and Working Group on Forecasting

monthly release of a real-time coincident indicator of the euro area business cycle. A notable difference however, is that our indicator may be subject to revisions over the past if individual series are strongly revised for example. This issue is largely discussed in the paper, and several quantifications of the revisions of the indicator are provided. This represents the main contribution of our work, as exploring the size of revisions of an elaborate tool is rather rare in the literature. Empirical studies tend to only focus on the forecasting performance of a tool by targeting the growth rate of GDP or industrial production index for instance. Another contribution of our work is of course the creation of an indicator for the Luxembourg economy that is, to the best of our knowledge, the all-first one. Several means have been used to evaluate its forecasting performances. The results give clear evidence that our indicator allow to obtain better forecasts of the GDP growth relative to a benchmark model relying on GDP past values only.

The paper is organized as follows. Section two presents the model. Section three presents the data and the main results of the estimation. All technical details have been skipped, and are discussed in the appendices 1 and 2. Section four is dedicated to the ex-post analysis of the Luxembourg business cycle. Section five focuses on the real-time use of the indicator. We explain how the monthly indicator may be calculated when (GDP) data is missing at the end of the sample. Section six provides quantifications of the revisions of the indicator. Finally, section 7 focuses on its pseudo-real-time forecasting performance. The last section concludes and raises some questions for pursuing further research.

2 The model

The model used to construct the indicator of economic activity for Luxembourg is the Generalized Dynamic-Factor Model (GDFM) of Forni *et alii* (2005). Let y_{nt}, $n = 1...N$ denotes one of a set of N zero-mean first-order stationary times series. For convenience, we suppose here that $y_{nt}, n = 1...N$ has unit variance. The GDFM assumes that each of these N times series may be represented as the sum of two mutually orthogonal unobservable components:

$$y_{nt} = c_{nt} + s_{nt}, n = 1...N \tag{1}$$

where c_{nt} and s_{nt} represent the common and idiosyncratic components of y_{nt}. For each n, these two components are zero-mean stationary processes. The model also assumes that the N common components are exclusively driven by past and present values of Q orthogonal common factors. These Q factors may be seen as the fundamental shocks shared by the N series. The factors, denoted $\{f_{qt}, q = 1...Q\}$, are supposed to be mutually-orthogonal white noise processes at all leads and lags and be characterized by unit variance. They explain the common component of each individual series as follows:

$$c_{nt} = \sum_{q=1}^{Q} \phi_{nq}(L) f_{qt}, n = 1...N \tag{2}$$

where the lag-operator polynomial $\phi_{nq}(L)$ are one-sided in L and their coefficients are square summable. For each n and each q, the polynomial admits the following representation: $\phi_{nq}(L) = \phi_{nq0} + \phi_{nq1}L + \phi_{nq2}L^2 + ... + \phi_{nqs}L^s$. The terms $(\phi_{nq0}, ..., \phi_{nqs}L^s)$ at the right side of equation (2) are called the dynamic loadings. They determine the contribution of factor f_{qt} to series y_{nt} in terms of both duration and magnitude. There are two main assumptions that characterise the GDFM: (A1) the common factors and the idiosyncratic components of any series are uncorrelated at all leads and lags; and (A2) the idiosyncratic components are at the most weakly cross-correlated. Additional assumptions and conditions required for the identification of the model are discussed in Forni *et alii* (2000 and 2005). Technical details related to the estimation of the GDFM are discussed in appendix 1.

3 The data and main results

The data set is made up of 99 series. It includes one quarterly series, real GDP, and 98 monthly series. The latter can be categorised in nine subgroups: industrial production; prices; turnover; wages and salary costs; new orders; financial series; external trade, and miscellaneous series (essentially car registrations and building permits). The complete list of 98 monthly series is reported in tables 6 to 8 of appendix 1. For the 98 monthly series, the data treatment consists of three steps. First, Tramo/Seats has been used to clean the data from both possible outliers and seasonality. Second, all series have been transformed by taking the first difference either in logs or in levels. The latter transformation has been used for interest and exchange rates and business surveys. Third, the data were standardized, that is expressed as deviations from mean and divided by their standard deviation. The quarter-on-quarter growth of real (seasonally-adjusted) GDP has been linearly interpolated to obtain a monthly series, and also standardized.

The model has been estimated using a dataset of 99 series covering the period from June 1995 to June 2007. We have retained a number of three dynamic factors, which explain more than 55 percent of the total variance of the 99 series (see appendix 2 for the detailed results of the estimation). The degree of commonality corresponds to the share of individual series' variance explained by its common component, that is $var\left(c_{nt}\right)/var\left(y_{nt}\right)$. In column 3 of tables 9 to 11 in the appendix 3 we can see that the degree of commonality of the individual variables ranges between 33.9 percent and 90.2 percent. GDP has a relatively high degree of commonality as its common component represents nearly 60 percent of its total variance. There are several series for which that percentage is even higher, especially in the price indices group.

Taking GDP as the reference series, the 98 other series can be classified according to their common component behavior related to that of GDP (see for instance Forni *et alii*, 2000b). The fourth columns of tables 9 to 11 show that 16 out of 98 series are classified as coincident, 25 are leading and 56 are lagging. From the business surveys group, we find that four series are leading and five are coincident. This finding confirms the popular intuition that business surveys data are of a particular interest in studying business cycles. It is important to notice this since Luxembourg has been often excluded from studies based on European business survey data as well as from the literature dedicated to business cycle analysis (noticeable exceptions are de Bandt *et alii*, 2006 and Marcellino, 2006). This idea that business surveys are a valuable source of information is very popular in Europe, but studies have mostly been limited to aggregate European data or only the larger member states (see Grenouilleau, 2004 and Forni *et alii*, 2001, for instance).

4 The indicator of economic activity for Luxembourg

4.1 Ex post analysis of the Luxembourg business cycle

Our aim is to assess the current economic situation in Luxembourg by a single indicator, which is less volatile than GDP and thus more informative (see BCL, 2007 and Nguiffo-Boyom, 2007a and 2007b). The focus is on medium- to long-run developments of the economy rather than quarter-on-quarter (qoq) movements that are more volatile and therefore more easily reversed in the short-run. Therefore, our indicator for Luxembourg is obtained by removing the most volatile movements of the common component $\hat{c}_{t,gdp}$, as of now called the raw indicator. We use the Christiano and Fitzgerald (2003) full-sample asymmetric version of Baxter-King band-pass filter to eliminate high frequency variations which last 18 months and less from the raw indicator. The indicator obtained over the period June 1995-June 2007, is by construction centered on zero. Positive (negative) values of the indicator indicate economic activity growing above (below) its historical mean. This historical mean is compatible with a quarterly growth of GDP of about 1.1 percent.

The indicator is visible in figure 1. On figure 1 (at the top left), it is presented in its monthly version. On figure 1 (at the top right), we can see the quarterly version of the indicator[2] together with the quarterly Luxembourg GDP quarter-on-quarter standardized growth rate. The business cycle in Luxembourg is visible as an alternation of increasing and decreasing phases of economic activity. The monthly indicator reflects the strong growth of the years 1999-2000, which were marked by a boom in the financial sector. The slowdown of activity at the end of year 1999-beginning of 2000 then continued until 2003. The indicator even reached its absolute minimum in January 2003. This extended slowdown was mainly due to the international context reflecting developments in Luxembourg's main trading partners. Between 1999 and 2003, Luxembourg faced the collapse of technological stock markets together with the quasi-stagnation of the more general stock indexes -such as the Dow-Jones and the CAC 40- in 2000; the September 11 attacks and the following climate of uncertainty; and the financial scandal due to accounting fraud. Finally, the recovery of the indicator in 2003 is consistent with the revival of the main stock-market indices. Since then, the indicator has continued to fluctuate in a manner that is relatively quiet in comparison to the ones of the period 1995-2003. On figure 1 (on the bottom left), the indicator is shown together with the indicator of the Banque Nationale de Belgique (BNB), and on figure 1 (on the bottom right) together with the Eurocoin. It appears that the indicator of the Luxembourg economy is a leading series relative to both the BNB (three months) and the Eurocoin (6 months). The correlation coefficients are indeed maximized at lags three and six and respectively reach 0.82 and 0.76. These results must nevertheless be considered very cautiously as both Eurocoin and the indicator of the Banque Nationale de Belgique are real-time indicators that are never revised while the indicator for Luxembourg is estimated ex-post.

4.2 Ex-post in-sample forecasting of GDP

In this section we evaluate the forecasting properties of the indicator. Simple regressions linking the GDP qoq growth (ΔGDP) to the indicator are common tools to explore the ex-post forecasting properties of the indicator. Equations have been estimated at a quarterly frequency, which requires

[2]It is constructed using a simple moving average of its monthly values over the quarter

Figure 1: The indicator of economic activity for Luxembourg - Monthly and quarterly version

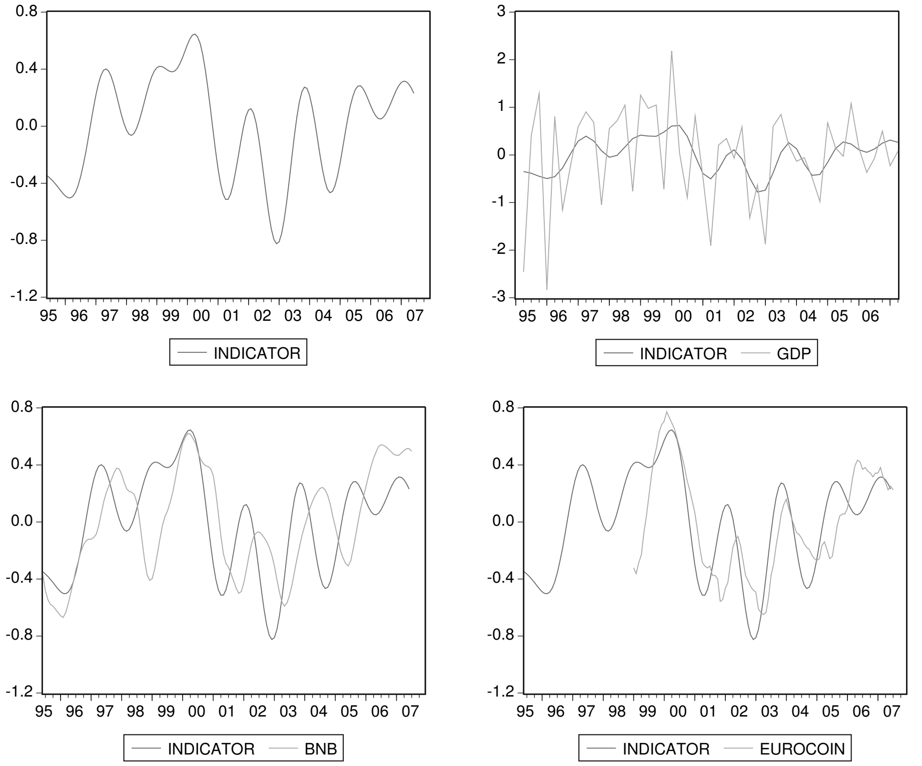


Table 1: Relative RMSEs - Ex-post in sample calculations *(1995Q2-2007Q2)*

Forecasting Horizons	Relative RMSE (AR)	Relative RMSE (RW)
H=0	0,669*	0,633*
H=1	0,707*	0,677**
H=2	0,837*	0,841**

*(**) indicates rejection of the DM test of the null hypothesis of equal forecasting accuracy at 5 percent(10 percent).

aggregating the monthly indicator. We denote IND_t the quarterly indicator constructed using a simple moving average of monthly values over the quarter, and estimate the following equation:

$$\Delta GDP_t = c + \psi(L) IND_t \tag{3}$$

where c represents the constant term and the order of the lag-operator polynomial $\psi(L)$ was determined using the Akaike criteria considering lags up to order eight. A polynomial of order one seems adequate to explain quarter-on-quarter GDP growth. In order to assess the relative forecasting properties of the indicator for zero to two quarters ahead, we produce forecasts using the following equation

$$\Delta GDP_{t+h} = c + \psi_0 IND_t + \psi_1 IND_{t-1}, h = 0, 1, 2 \tag{4}$$

and we also generate forecasts from both a Random Walk (RW) model and an Autoregressive with constant (AR) benchmark models of ΔGDP. The Akaike criteria leads us to fix the AR order-lag parameter to four. The table 1 reports the relative in-sample Root Mean Squared Errors (RMSE) zero to two quarters ahead relative to those of the AR and RW models. It appears that including current and past values of the indicator in an equation for describing GDP qoq growth reduces forecasting errors in comparison with the two univariate approaches exclusively based on GDP past values. The Diebold-Mariano (DM) test (Diebold and Mariano, 1995) is used to compare the accuracy of in-sample forecasts of the indicator against both benchmark models. It results that for zero to two quarters horizon, the AR model does not outperform the indicator-based equation. When considering the RW model as benchmark, the DM test fails to reject at five percent the null hypothesis of equal forecasting accuracy for both one and two quarters horizons.

5 Real-time use of the indicator

Our objective is to release a monthly indicator of economic activity based on the large number of time series included in our dataset. We aim at releasing at the beginning of each month T the indicator for the month $T-1$. In practice, we expect to face unbalanced end-of-sample issues. First, the dates of release may differ from one series to another[3]. Second, monthly data are published with different delays with respect to their reference period. For instance financial variables and business surveys are released right at the end of the month whereas production indices are available with a delay of about six weeks. On the other hand, GDP is published on a quarterly basis with a delay longer than three months. On the 10 October 2007 for instance, GDP figures for the second quarters of 2007 have been published; while business survey and financial data were available until September 2007, and production indices and labor market series were available until respectively July and August 2007. It is therefore necessary to take full account of the timing of data releases in constructing the indicator. We decided to proceed as follows:

Step 1. Updating the database. The 98 monthly series of the dataset are downloaded the last day of the month, so that both financial and business survey data for the current month are available. GDP is also downloaded when the quarterly national accounts are published, that is four times a year around the beginning of January, April, July and August. The GDP quarter-on-quarter growth rate is converted to a monthly frequency by a linear interpolation, which attributes the quarterly growth rate observation to the last month of the corresponding quarter. In our dataset GDP is the series with the largest delay of publication. It will therefore determine the dates at which sample data is balanced because all series are available; and those after which it is unbalanced because delays of publication differ from one series to another. As the data timing issue is easier to explain with an example, we consider the timing of the year 2007 (see table 2). Let T denote the beginning of the month. As shown by the second and third column of table 2, the structure of the GDP release implies that the length of the balanced part of the dataset sample remains constant throughout the quarter. As for the incomplete part of the dataset sample, it mechanically grows throughout the quarter as new monthly observations are additionally released. This will of course determine the way the indicator is calculated.

Step 2. Release of the indicator. The indicator for $t = 1, ..., T-1$

[3]For example see the STATEC calendar of publication, which is available on the website www.statistiques.public.lu/fr/functions/calendrier

Table 2: 2007 Timing of indicator both calculations and projections

Beginning of Month T	GDP release	Last point of balanced sample	Last point of indicator estimate	Projections from	to
Jan-07	2006-Q3	2006:09	T-4	T-3	T-1
Feb-07	-	2006:09	T-5	T-4	T-1
Mar-07	-	2006:09	T-6	T-5	T-1
Apr-07	2006-Q4	2006:12	T-4	T-3	T-1
May-07	-	2006:12	T-5	T-4	T-1
Jun-07	-	2006:12	T-6	T-5	T-1
Jul-07	2007-Q1	2007:03	T-4	T-3	T-1
Aug-07	-	2007:03	T-5	T-4	T-1
Sep-07	-	2007:03	T-6	T-5	T-1
Oct-07	2007-Q2	2007:06	T-4	T-3	T-1
Nov-07	-	2007:06	T-5	T-4	T-1
Dec-07	-	2007:06	T-6	T-5	T-1

is updated at the beginning of month T. Given the recurrent end-of-sample unbalances of our dataset, we consider in each month first the balanced part of the sample and, thereafter, the unbalanced one.

Each month T, the indicator is estimated over a period that corresponds to the one recovered by the balanced part of the dataset. This period begins at $t = 1$ and ends at the date for which the last observation of the monthly GDP is available. Given the three firsts columns of table 2, we deduce easily that at each month T the indicator is calculated until $T - k$, with $k = 4, 5$ or 6 according to the position of the month T in the quarter (see column four of the table). Hence, in October 2007, the indicator was calculated until June 2007 (T-4).

Thereafter, for periods $T - k + 1, ..., T - 1$, the number of missing observations at the end of sample differs across the series since monthly data are published with different delays. In the beginning of month T for instance, business surveys are indeed available until $T - 1$ but industrial production only until $T - 3$. The idea is making use of the monthly-series-related last information for projecting the indicator until $T - 1$. We adopt the strategy proposed by Altissimo *et alii* (2001), which involves the re-alignment of the 99 series before exploiting the variance-covariance matrix structure of their common component. The principle is simply to shift the variables forward in time to eliminate missing observations in the most recent periods. Let k_n be the release delay[4] (in months) for the variable y_{nt}. At the end of the sample

[4]For $n = GDP$, we set that $k_n = k$, $k = 4, 5$ or 6

T, the last available observation of y_{nt} will therefore be $y_{n,T-k_n}$. By setting $y^*_{nt} = y_{n,T-k_n}$ for $n = 1,...,N$ we obtain a re-balanced[5] sample of data in which the last available observation of y^*_{nt} is at T for each n. The re-aligned vector of data Y^*_T is obtained after having collected all the y^*_{nt}. Then the generalized principal components are computed for Y^*_T; and thereafter, formula (16) is used to obtain the $k-1$ remaining values of the raw indicator: $\hat{C}^*_{T+h} = \hat{\Gamma}^*_C(h)\, V^* \left(V^{*\prime}\hat{\Gamma}^*(0)V^*\right)^{-1} V^{*\prime}Y^*_T$. In summary, the values of the indicator for the period $[1, T-1]$ may be available at the beginning of month T, even if GDP and other monthly series are not available until $T-1$. The last 3 (4 or 5) observations of the indicator that are released at the beginning of the first (second or third) month of the quarter have to been considered as provisional, as they result from projections of the indicator that exploit the dynamic covariance structure of the series' common components. Basically, these last 3 (4 or 5) observations of the indicator give an information on the current relative state of the economy, given the latest available information.

6 Quantifying revisions of the indicator

A business cycle indicator must track economic developments and provide a diagnostic on the current economic situation. Nowcasting economic activity in real-time represents an important challenge for economic and monetary authorities in choosing the appropriate policy stance. GDP is often considered the reference series for tracking business cycle movements. However, it is released on a quarterly frequency with a considerable delay and may be subject to significant revision afterwards. The 98 other series we use are released with shorter publication delays, but are nevertheless also revised each month due to seasonal adjustment. This means that the indicator will also be subject to revisions -as new data observations are available and as data is still revised. Exploring the size of revisions of an elaborate tool such as our indicator is rather rare in the literature[6]. Empirical studies tend to only focus on the forecasting performance of a tool by targeting the growth rate of GDP or the industrial production index for instance (see Marcellino, 2005, for an overview of the evaluation of leading indicators). Among the rare exceptions, we notice that Diron (2006) evaluates the impact of data revisions on short-term forecasts of GDP growth and Giannone, Reichlin and Small

[5]This re-alignment implies of course cutting some observations at the beginning of the sample for some variables.

[6]Real-time studies are more common in the slightly different context of evaluating the reliability of output gap real-time estimates (see Ruenstler, 2007 and Planas and Rossi, 2004)

(2006) study the impact of new information availability (due to new data releases throughout the month) on nowcasts and forecasts of both output and inflation. In the present case, we propose a decomposition of revisions of the indicator that are due to the uncertainty of individual series. For that objective, the assessment of data uncertainty is made by focusing on the errors in pseudo-real-time concurrent estimates (using the October 2007 vintage data as reference). For simplicity, all calculations in this section assume that at each period t the end of sample is balanced. We concentrate on the Root Mean Squared Revision (RMSR) that we define as

$$RMSR = \sqrt{\sum_{t=1}^{T} \left(ind_{T|T+k} - ind_{T|T}\right)^2 / T} \tag{5}$$

where $ind_{T|T}$ is the concurrent estimate of the indicator at time T using all information available up to T, and $ind_{T|T+k}$ its estimate calculated k periods later. The difference $ind_{T|T+k} - ind_{T|T}$ represents the total revision after k periods. In the following, we will rather consider the Absolute Revision of Last Observation (ARLO) that we define as

$$ARLO = |ind_{T|T+k} - ind_{T|T}| \tag{6}$$

in order to measure the magnitude of end-of-sample revisions.

In a first stage, we consider uncertainty due to the release of new data observations. In our case, the monthly frequency of data releases implies that each month, 98 additional observations are available. We therefore estimate the indicator recursively by taking into account these new observations. In a second stage, we also consider real-time statistical treatment of the data focusing on monthly seasonally adjustment and identification plus removal of outliers. In the third and last stage, revisions to quarterly national accounts are also taken into account in addition to the monthly statistical treatment of the series. Nine successive vintages of quarterly GDP have been released in Luxembourg so far. This last exercise can also be considered a (pseudo) real-time measure of the average revision in the indicator. It is indeed a real-time exercise since it reproduces the information that was available the days the nine different GDP vintages were released. However, it is not a genuine real-time exercise but only a pseudo-real-time one since it uses the October 2007 version of the 98 monthly series. These ones have of course been revised since then. The results of the simulations are presented in table 3. They show that the monthly addition of 98 new observations affect past and present values of the (smoothed) indicator. On average, the magnitude of the revision is quite modest (0.057). Nevertheless, the last 12 observations of the indicator tend to be revised relatively more, with a magnitude that is (at 0.096) close to 0.10 percentage point. As for the statistical treatment, it does not seem to be an additional factor contributing to the revisions of the indicator. GDP revisions, for themselves, appear to account for most of the revisions in the indicator. For instance, between the two last quarterly national accounts releases[7], the RMSR reached nearly 0.30 point. However, this last figure deserves to be put in perspective as it fell to 0.15 percentage point when all GDP revision episodes[8] are taken into account. Over the same period the RMSR of GDP reaches 0.9 percentage point. Another interesting result shown in table 3 is the benefits of smoothing that is used for removing the most volatile movements of the raw indicator. The average ARLO of the (smoothed) indicator is more than two times smaller at stage three of the exercise in comparison to those of the raw indicator. It appears also that smoothing reduces the average RMSR. These last results are quite conform to the intuition since the objective of smoothing is eliminating noise from a series. Nevertheless, it is interesting to discuss these results as a commonly recognized drawbacks of Band-Pass filters is that they cause strong end-of sample effects in the output series. In the present case, we show that they allow to mechanically minimize the magnitude of revisions.

7 Pseudo-real-time forecasting of GDP

The objective here is to verify whether the indicator would have been useful to predict GDP growth using regression models. Before pursuing, we should keep in mind three things. First, this exercise is only one way to evaluate our indicator. Second, it does not challenge our original aim of tracking medium- to long-run developments on a monthly basis rather than forecasting specific GDP releases. Third, the approach used here is quite similar to that adopted in section 4.1 in so far as we estimate regressions linking qoq GDP growth to the indicator. However, one difference is that the specification of the equation is recursively determined. A second difference is that here we give special attention to the unbalanced end-of-sample issue. In the context of this exercise, we explicitly suppose that the structure of the current calendar of data releases is the same as those which prevailed previously. In this section we report the results of a pseudo-real time forecasting exercise using the vintage data, which were available at the beginning of October 2007. This is a pseudo real-time forecast evaluation exercise, as it takes full account

[7] 6 July and 10 October 2007

[8] That is the eight publications of quarterly accounts that occur since the first one on 25 April 2005

Table 3: Evaluation of revisions in concurrent estimates

Stage 1: Recursive analysis - Ex post SA data and final GDP data

		ARLO		RMSR	
Date of release	T	Raw Indicator	Indicator	Raw Indicator	Indicator
25-Apr-05	Q4-2004	0.138	0.246	0.149	0.103
21-Jul-05	Q1-2005	0.031	0.095	0.143	0.089
28-Apr-06	Q4-2005	0.120	0.009	0.106	0.067
17-Jul-06	Q1-2006	0.050	0.124	0.072	0.051
06-Oct-06	Q2-2006	0.091	0.002	0.061	0.043
10-Jan-07	Q3-2006	0.011	0.095	0.064	0.041
05-Apr-07	Q4-2006	0.082	0.140	0.064	0.039
06-Jul-07	Q1-2007	0.110	0.055	0.045	0.020
	Average	0.079	0.096	0.088	0.057

Stage 2: Recursive analysis - Recursive SA data and final GDP data

		ARLO		RMSR	
Date of release	T	Raw Indicator	Indicator	Raw Indicator	Indicator
25-Apr-05	Q4-2004	0.051	0.230	0.178	0.104
21-Jul-05	Q1-2005	0.063	0.084	0.182	0.089
28-Apr-06	Q4-2005	0.321	0.099	0.137	0.049
17-Jul-06	Q1-2006	0.071	0.072	0.115	0.074
06-Oct-06	Q2-2006	0.058	0.008	0.100	0.042
10-Jan-07	Q3-2006	0.000	0.095	0.100	0.054
05-Apr-07	Q4-2006	0.066	0.102	0.092	0.043
06-Jul-07	Q1-2007	0.107	0.049	0.052	0.018
	Average	0.092	0.092	0.119	0.059

Stage 3: Recursive analysis - Recursive SA data and GDP revisions

		ARLO		RMSR	
Date of release	T	Raw Indicator	Indicator	Raw Indicator	Indicator
25-Apr-05	Q4-2004	0.896	0.473	0.589	0.270
21-Jul-05	Q1-2005	0.682	0.152	0.568	0.210
28-Apr-06	Q4-2005	0.656	0.038	0.234	0.060
17-Jul-06	Q1-2006	0.088	0.229	0.205	0.069
06-Oct-06	Q2-2006	0.061	0.001	0.203	0.096
10-Jan-07	Q3-2006	0.024	0.054	0.234	0.154
05-Apr-07	Q4-2006	0.152	0.108	0.182	0.086
06-Jul-07	Q1-2007	0.333	0.133	0.425	0.274
	Average	0.361	0.148	0.330	0.152

Table 4: Relative Root Mean Squared Errors - Pseudo-real-time calculations *(2005Q1-2007Q2)*

Quarters to forecast	Average relative RMSE (AR)	Average relative RMSE (RW)
Preceding quarter	0,832*	0,794**
Current quarter	0,841*	0,524**
Next quarter	0,834*	0,963*

*(**) indicates rejection of the DM test of null hypothesis of equal forecasting accuracy at 5 percent (10 percent).

of the timing of data releases by fully replicating real-time data availability patterns when producing the recursive forecasts. It is a pseudo(real-time) exercise because the data are downloaded on a certain day so that subsequent revisions to the initial data releases are ignored. This corresponds to the approach used by the WGEM/WGF short-term forecasting team to evaluate models. The table 4 shows the average RMSE for preceding, current and next quarter forecasts relative to those of the benchmarks: an AR model that is recursively estimated and a random walk (RW) model. It appears that the information encapsulated in the indicator allows a systematic reduction in the forecast errors. It outperforms the benchmark AR model in terms of forecasting ability for all forecast horizons considered and the RMSE is reduced by nearly 16 percent on average. The DM test confirms that the prediction obtained with the indicator are significantly more accurate than those of the AR model. This outperformance is less evident when considering the RW model as a benchmark, since the DM test does not allow rejecting the null hypothesis of equal forecasting accuracy for both preceding and current quarters at five percent.

8 Concluding remarks

We have elaborated a monthly indicator of economic activity for Luxembourg using a variety of economic and financial data in addition to the GDP. We have used a purely statistical approach to summarize the information contained in our large dataset, the generalized dynamic factor model introduced by Forni *et alii* (2005). The obtained indicator for Luxembourg has been evaluated in different ways. First, we have evaluated its forecasting performances both in-sample and out-of-sample. Second, we have evaluated the real-time use of the indicator. Finally, we have quantified the potential sources of revision to the indicator. The results are encouraging as the performances of our indicator are satisfactory. The indicator has also been subject to revisions which may on occasion be substantial. However, these revisions have been modest relative to those of the GDP quarter-on-quarter growth that have been released by the Luxembourg national institute of statistics.

A variety of variations and extensions of our indicator may be envisaged. Firstly, we would like to extend back the period of analysis and study the development of the Luxembourg economy over a longer period. Secondly, we would like to investigate further models, including dynamic factor model versions that differ from the one used in this paper. Finally, we hope that this work will stimulate research dedicated to the Luxembourg business cycle and contribute to enhance our capability to nowcast the state of the Luxembourg economy.

References

[1] Altissimo F., A. Bassanetti, R. Cristadoro, M. Forni, M. Lippi, L. Reichlin and G. Veronese (2001): *EuroCOIN: A real time coincident indicator of the euro area business cycle*, CEPR Discussion Paper 3108, December 2001.

[2] Altissimo, F., R. Cristadoro, M. Forni, M. Lippi, and G. Veronese (2006): *New EuroCOIN: tracking Economic growth in real time*, CEPR Discussion Paper 5633, December 2006.

[3] Bai, J. and S. Ng (2002): *Determining the number of factors in approximate factor models*, Econometrica, **70**(1), 191221.

[4] Bai, J. and S. Ng (2007): *Determining the Number of primitive Shocks in Factor Models*, Journal of Business and Economic Statistics, **25**(1), American Statistical Association, January 2007, pp.52-60.

[5] BCL (2007): *Rapport Annuel 2006*, Banque centrale du Luxembourg, June 2007.

[6] de Bandt O., Bruneau C. and Flageolet A. (2006): *Assessing aggregate comovements in France, Germany and Italy using a non stationary factor model of the euro area*, Notes d'étude et de recherche No. 145, Banque de France, June 2006.

[7] Bruneau C., de Bandt O., Flageolet A. and Michaux, E. (2003): *Forecasting inflation using economic indicators: the case of France*, Notes d'étude et de recherche No. 101, Banque de France, May 2003.

[8] Christiano, L. and T. Fitzgerald (2003): *The Band Pass Filter*, International Economic Review, **44**(2), pp. 435-465.

[9] Cristadoro, R., M. Forni, L. Reichlin and G. Veronese (2005): *A core inflation index for the euro area*, Journal of Money, Credit and Banking, **37**(3), pp. 539-560.

[10] Den Reijer, A. (2005): *Forecasting dutch GDP using large scale factor models*, De Nederlandsche Bank Working Paper series No. 28, February 2005.

[11] Diebold, F. and R. S. Mariano (2002): *Comparing Predictive Accuracy*, Journal of Business and Economic Statistics, **20**(1), pp. 134-144.

[12] Diebold, F. and Rudebusch G. (1996): *Measuring Business Cycles: aModern Perspective*, The Review of Economics and Statistics, **78**, February, pp. 66-77.

[13] Diron M. (2006): *Short-term forecasts of euro area real GDP growth. An assessment of real-time performance based on vintage data*, ECB Working Paper series No. 622, May 2006.

[14] Doz C., D. Giannone and L. Reichlin (2003): A quasi maximum likelihood approach for large approximate dynamic factor models, CEPR Discussion Paper 5724, June 2006.

[15] Forni M., M. Hallin, M. Lippi and L. Reichlin (2000): *The generalized dynamic factor model: Identification and estimation*, The Review of Economics and Statistics, **82**(4), pp.540-554.

[16] Forni M., M. Hallin, M. Lippi and L. Reichlin (2000b): *Reference Cycles: The NBER Methodology Revisited*, CEPR Discussion Paper 2400, January 2000.

[17] Forni M., M. Hallin, M. Lippi and L. Reichlin (2001): *Coincident and Leading indicators for the Euro Area*, The Economic Journal, **111**, pp.62-85.

[18] Forni, M., Hallin M., Lippi M. and L. Reichlin (2005): *The generalized dynamic factor model: one-sided estimation and forecasting*, Journal of the American Statistical Association, **100**, pp.830-840.

[19] GIANNONE, D. AND MATHESON T. (2007): *A New Core Inflation Indicator for New Zealand*, International Journal of Central Banking, **37**(3), December 2007, pp. 145-180.

[20] GIANNONE D., L. REICHLIN AND D. SMALL (2006): *Nowcasting GDP and inflation. The real-time informational content of macroeconomic data releases*, ECB Working Paper series No. 633, May 2006.

[21] GRENOUILLEAU D. (2004): *A Sorted Leading Indicators Dynamic (SLID) Factor Model for short-run Euro-area GDP Forecasting*, European Commission Economic Paper 219.

[22] GEWEKE J. (1977): *The Dynamic Factor Analysis of Economic Time Series Models*, in Latent Variables in Socioeconomic Models, North Holland, pp.365-383.

[23] HALLIN, M. AND R. LISKA (2007): *Determining the Number of Factors in the Generalized Factor Model*, Journal of the American Statistical Association, **102**(478), pp.603-617.

[24] KIM, C.-J AND C. NELSON (1998): *Business cycle turning points, a new coincident index, and tests of duration dependence based on a dynamic factor model with regime switching*, The Review of Economics and Statistics, **80**, pp. 188-201.

[25] MARCELLINO, M. (2005): *Leading indicators: What have we learned?*, CEPR Discussion Paper No. 4977, London, Centre for Economic Policy Research.

[26] MARCELLINO, M. (2006): *Dynamic factor Models for Survey-based Confidence indicators, Final report*, Manuscript, November 2006.

[27] NGUIFFO-BOYOM, M. (2007A): *Un indicateur d'activité pour le Luxembourg*, Bulletin de la Banque centrale du Luxembourg, **2007** (1), September 2007.

[28] NGUIFFO-BOYOM, M. (2007B): *Résumé non-technique du cahier d'étude : Un indicateur d'activité pour le Luxembourg*, Bulletin de la Banque centrale du Luxembourg, **2007** (2), December 2007.

[29] PLANAS, C. AND A. ROSSI (2004): *Can inflation data improve the real-time reliability of output gap estimates?*, Journal of Applied Econometrics, **19**, pp.121-133.

[30] Ruenstler G. (2002): *The information content of real-time output gap estimates, an application to the euro area*, ECB Monthly Bulletin, **182**, European Central Bank, September 2002.

[31] Ruenstler G., K. Barhoumi, S. Benk, R. Cristadoro, A. Den Reijer, A. Jakaitiene , P. Jelonek, , A. Rua, K. Ruth, and C. Van Nieuwenhuyze(2007): *Short-term forecasting of GDP using large data sets: A pseudo real-time forecast evaluation exercise*, *Forthcoming* in European Central Bank Occasional Paper.

[32] Schneider, M. and M. Spitzer (2004): *Forecasting Austrian GDP using the Generalized Dynamic Factor Model*, Oesterreichische National-Bank Working Paper 89, September 2004.

[33] Sargent, T. J. and C. A. Sims (1977): *Business Cycle Modeling Without Pretending to have too Much a priori Economic Theory*, in New Methods in Business Cycles Research, Federal Reserve Bank of Minneapolis, pp. 45-110.

[34] Schumacher C. (2005): *Forecasting German GDP using alternative factor models based on large datasets*, Deutsche Bundesbank Discussion Paper 24/2005.

[35] Schumacher, C. and J. Breitung (2006): *Real-time forecasting of GDP based on large factor model based model with monthly and quarterly data*, Deutsche Bundesbank Discussion Paper 33/2006.

[36] Stock, J. and M. Watson (2002a): *Macroeconomic forecasting using diffusion indexes*, in Journal of business and Economic Statistics, **20**, pp. 147-162.

[37] Stock, J. and M. Watson (2002b): *Macroeconomic forecasting using principal components from a large number of predictors*, in Journal of the American Statistical Association, **97**, pp. 1167-1179.

[38] Van Nieuwenhuyze, C.(2006): *A generalized dynamic factor model for the Belgian economy - Useful business cycle indicators and GDP growth forecasts*, National Bank of Belgium Working Paper Research No. 80, February 2006.

A Appendix 1: Estimating the common components

The non-parametric approach proposed in Forni *et alii* (2005) allows identification of the common and idiosyncratic components of the GDFM defined by equations (1) and (2), as the cross-section (N) and the time (T) dimensions go to infinity. The advantage of their approach is that it provides consistent estimates of the components not only as both N and T go to infinity at some rate, but also when T is relatively small, possibly smaller than N. There are two steps to identify common components.

Step 1. Estimating the spectral density matrix of the common components. First, spectral density matrix of observed series $Y_t = (y_{1t}, ..., y_{Nt})'$ is estimated over a set of frequencies θ_h by applying a discrete Fourier transform to the sample auto-covariance matrices of Y_t:

$$\hat{\Sigma}_Y(\theta_h) = \frac{1}{2\pi} \sum_{k=-M}^{M} \omega_k \Gamma(k) e^{-i\theta_h}, h = 0, 1, ..., 2M \quad (7)$$

where $\Gamma(k)$ is the sample covariance matrix of Y_t and Y_{t-k}; integer M is the length of the Bartlett lag window; and $\omega_k = 1 - (|k|/M + 1)$ are the Bartlett lag window estimator weights. θ_h is the frequency at which spectral density matrix is evaluated. Note that the spectra are evaluated at $2M + 1$ equally spaced frequencies in the interval $[-\pi, \pi]$.

Second, a dynamic principal components decomposition of each spectral density matrix is performed: for each h, $\hat{\Sigma}_Y(\theta_h)$ is diagonalized, and its eigenvalues $\lambda_j(\theta_h), j = 1, ..., N$ and associated eigenvectors $p_j(\theta_h), j = 1, ..., N$ are computed. By first ordering the eigenvalues in descending order for each frequency and then, collecting values corresponding to different frequencies, eigenvalue and eigenvector functions of θ are defined. These functions are respectively denoted $\lambda_j(\theta)$ and $p_j(\theta), j = 1, ..., N$. For each component, the ratio of its eigenvalue function to the sum of all eigenvalues functions defines its contribution to the total variance in the system:

$$R_j = \int_{-\pi}^{\pi} \lambda_j(\theta) d\theta / \sum_{j=1}^{N} \int_{-\pi}^{\pi} \lambda_j(\theta) d\theta \quad (8)$$

Third, one chooses a value Q for the number of dynamic factors using an eigenvalue-based criterion. For instance, the average over θ of the first Q empirical eigenvalues may diverge, while the average over the $(Q+1)-th$ one is relatively stable; or there may be a substantial gap between the variance explained by principal component Q and the variance explained by principal component $Q+1$[9].

Fourth, the spectral density matrix of the vector of the common components $C_t = (c_{1t}, ..., c_{Nt})'$ can be estimated using the matrix:

$$\hat{\Sigma}_C(\theta) = P(\theta)\,\Lambda(\theta)\,\tilde{P}(\theta) \tag{9}$$

where $\Lambda(\theta)$ is a $Q\times Q$ diagonal matrix having on the diagonal $\lambda_1(\theta)\ \lambda_2(\theta), ...,$ $\lambda_Q(\theta)$, $P(\theta) = (p_1(\theta)...p_Q(\theta))'$ is a $N \times Q$ matrix and $\tilde{P}(\theta)$ its conjugate transpose matrix. The spectral density matrix of idiosyncratic components $S_t = (s_{1t}, ..., s_{Nt})'$ is obtained as the following difference $\hat{\Sigma}_S(\theta) = \hat{\Sigma}_Y(\theta) - \hat{\Sigma}_C(\theta)$. Finally, the sample auto-covariance of C_t is obtained by applying the inverse discrete Fourier transform to the above estimated spectral density matrix:

$$\hat{\Gamma}_C(k) = \frac{2\pi}{2M+1}\sum_{h=-M}^{M}\hat{\Sigma}_C(\theta_h)\,e^{-ik\theta_h} \tag{10}$$

Step 2. Estimating and forecasting the common components. This second step requires the estimation of static factors to approximate the Q dynamic factors (or shocks) of the model[10]. For that purpose, past val-

[9]These criteria are suggested in Forni *et alii* (2000 and 2005). More sophisticated methods for the identification of Q have recently been proposed in the literature, notably by Bai and Ng (2002 and 2007) and Hallin and Liska (2007).

[10]Theoretical dynamic factors can be obtained by first expanding each eigenvalue's associated dynamic eigenvector $p_j(\theta_h), j = 1, ..., N$ in Fourier series as

$$p_j(\theta) = \frac{1}{2\pi}\sum_{k=-M}^{M}\left[\int_{-\pi}^{\pi}{}_j(\theta)\,e^{ik\theta}d\theta\right]e^{-ik\theta} \tag{11}$$

Second, transferring it to the time domain by applying an inverse Fourier transform:

$$\underline{p}_j(L) = \frac{1}{2\pi}\sum_{k=-M}^{M}\left[\int_{-\pi}^{\pi}{}_j(\theta)\,e^{ik\theta}d\theta\right]L^k \tag{12}$$

and finally:

$$\underline{p}_j(L)\,y_t = f_{jt} \tag{13}$$

It appears that dynamic factors are theoretically explained by both lagged and future values of observable series since the filters $\underline{p}_j(L), J = 1, ..., N$ are two-sided. The estimation of common components at the end and beginning of the sample is therefore not feasible if series are not available for $t < 0$ and $t > T$. For that reason, Forni *et alii* (2000 and 2005) propose an approximate of the common components, which is a one-sided filter of the observations.

ues of the common factors are here treated as separate static factors. We therefore consider now that $r = Q(s+1)$ shocks affect the system, namely $(f_1t, f_{1,t-1}, ..., f_{1,t-s}, f_2t, f_{2,t-1}, ..., f_{2,t-s}, ..., f_{Q,t-s})$. These static factors are obtained by taking the r generalised principal components of $\hat{\Gamma}_C(0)$: computing the generalised eigenvalues μ_j, i.e. the N complex numbers solving $det\left(\hat{\Gamma}_C(0) - z\hat{\Gamma}_S(0)\right) = 0$; and the corresponding generalised eigenvectors $V_j, j = 1, ..., N$ satisfying

$$V_j\hat{\Gamma}_C(0) = \mu_j V_j \hat{\Gamma}_S(0) \tag{14}$$

and the normalizing condition

$$V_j\hat{\Gamma}_S(0)\, V_i' = \begin{cases} 1 for j=i \\ 0 for j\neq i \end{cases} \tag{15}$$

After ordering the eigenvalues μ_j in descending order and taking the eigenvectors corresponding to the r largest eigenvalues, the static factors are estimated by the r generalised principal components $v_j = V_j', j = 1, ..., r$. These generalised principal components are the linear combination of the $y_{nt}, n = 1, ..., N$, having the smallest ratio of idiosyncratic to common variance (see Forni *et alii*, 2005). The generalised principal components together with the covariance matrices estimated in the first step provide both estimates and forecasts of C_t. Setting $V = (V_1 \cdots V_r)$ and $v_t = (v_{1t} \cdots v_{rt})'$, estimates of $C_{t+h}, h = 0, 1, .., s$ are given by

$$\hat{C}_{t+h} = \hat{\Gamma}_C(h)\, V \left(V'\hat{\Gamma}(0)V\right)^{-1} v_t = \hat{\Gamma}_C(h)\, V \left(V'\hat{\Gamma}(0)V\right)^{-1} V'Y_t \tag{16}$$

Forni *et alii* (2005) show that when both N and T go to infinity, $\hat{C}_t$ is a consistent estimate of C_t; and $\hat{C}_{t+h}$ converges to the theoretical projection of C_{t+h} on the past and present of $f_{1t}, ..., f_{Qt}$.

B Appendix 2: Results of estimation using the Luxembourg dataset

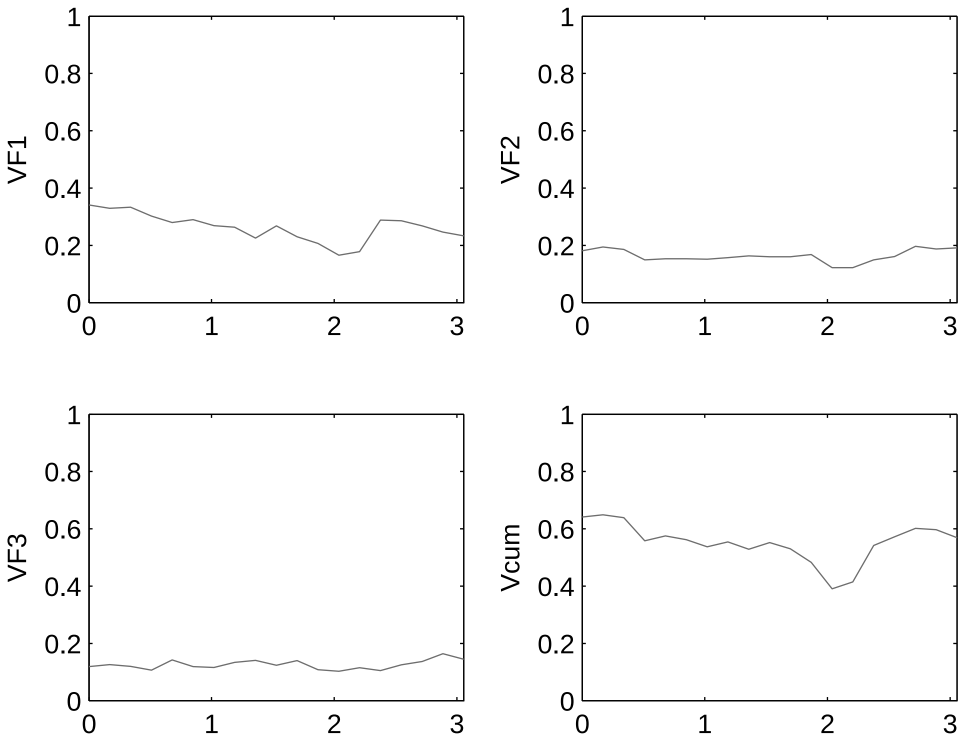
As discussed previously in the appendix 1, several parameters need to be chosen, namely the number of dynamic factors (Q) the size of the Bartlett window (M) which also determines the number $(2M+1)$ of frequencies at which the spectral density is evaluated in the interval $[-\pi, \pi]$. At this stage, there are no commonly used criteria to determine the value of M. On the one hand, Forni *et alii* (2000) suggests that M should be a function of T. According to the results of their simulations, M=*round*$\left(\frac{2}{3}T^{\frac{2}{3}}\right)$performs relatively well. As for Schneider and Spitzer (2004) and Van Nieuwenhuyze (2006), they choose the rule M=*round*$\left(\frac{1}{4}T^{\frac{1}{2}}\right)$. On the other hand, both Altissimo *et alii* (2001) and Altissimo *et alii* (2006) use a Bartlett lag-window of size 18 and 24 and respectively evaluate the spectral density at 101 and 121 frequencies. The former justifies their choices - for Q, M and the number of static factors r - by the results of a "pseudo real-time analysis".

In the present case, we set M=18. The spectra has therefore been evaluated at 37 equally spaced frequencies in the interval $[-\pi, +\pi]$ by using a Bartlett window of size 18 and the 18 lead/lag covariance matrix of observed data. We use the criteria suggested by Forni *et alii* (2000) to determine the number of common factors: Q is identified by requiring a minimum amount of explained variance for each dynamic components on average across all frequencies. This minimum was set at 10 percent. The results reported in table 5 show that at frequency 0, the first three dynamic factors explain more than 60 percent of the total variance of the 99 series. On average across all 37 frequencies, more than 50 percent of the total variance is explained by these three factors. As for the fourth dynamic factor and the following ones, they individually explain less than 10 percent of the total variance on average. We therefore consider $Q = 3$ dynamic factors. Figure 2 displays the contributions of the first three dynamic factors as well as their cumulated contribution to the series' total variance on the interval $[0, \pi]$. They are respectively denoted $VF1$, $VF2$, $VF3$ and $Vcum$. The average contribution across all frequencies θ of the first dynamic factor to the total variance is about 26 percent. For the second and third dynamic factors, these percentages are respectively about 16 and 13 percent. Overall, the first three dynamic factors explain more than 55 percent of the total variance over the interval $[0, \pi]$.

Table 5: Cumulated percentage of total variance explained

Number of dynamic factors	At frequency zero	Average across all frequencies
1	0.341	0.263
2	0.522	0.427
3	0.641	0.552
4	0.750	0.644
5	0.820	0.716
6	0.865	0.771
7	0.902	0.816
8	0.925	0.851
9	0.936	0.878
10	0.946	0.898

Figure 2: Share of variance explained by the first three dynamic eigenvalues



C Appendix 3: Data set and Mnemonics

Table 6: Data set

PERSPE	Business survey, industry: Employment expectations
CET	Business survey, industry: Export order-books
CTX	Business survey, industry: Total order-books
STO	Business survey, industry: Stocks of finished products
PERSP	Business survey, industry: Production expectations
TPPA	Business survey, industry: Production trend observed in recent months
PERSPX	Business survey, industry: Selling-prices expectations
ACPAS	Business survey, building: Trend of activity
CCOM	Business survey, building: Order books
EXPEM	Business survey, building: Employment expectations
EXPX	Business survey, building: Prices expectations
PJO-M	Production per working day: Manufacturing
PJO-K	Production per working day: Equipment goods
PJO-J	Production per working day: Energy
PJO-B	Production per working day: Building
PJO-TP	Production per working day: Civil engineering
PJO	Production per working day: Total industry excluding construction
PJO-I	Production per working day: Intermediate goods
IP	Industrial production index: Total industry excluding construction
IP-I	Industrial Production index, Intermediate goods Industry
YEMP-MA	Output per employee: Manufacturing
YEMP	Production per employee: Total industry excluding construction
YHR	Production per man hour: Manufacturing
YHRL	Production per man-hour: Total industry excluding construction
NICP	National index of consumer prices
OIL	Price of crude oil Europe (DTD BRENT)
PPI-DO	Industrial producer prices: Total industry on domestic market
PPI-X	Industrial producer prices: Total industry on exported goods
PPI-IX	Industrial producer prices: Total industry on exports outside EU
PPI	Industrial producer prices: Total industry excluding construction
PPI-I	Industrial producer prices: Intermediate goods
PPI-K	Industrial producer prices: Capital goods
PPI-C	Industrial producer prices: Consumer goods
PPI-BTP	Industrial producer prices: Construction input prices

Table 7: Data set *(continued)*

CA-B	Turnover: Building
CA-TP	Turnover: Civil engineering
CA-I	Turnover: Total industry excluding construction
CA-DET	Turnover: Retail trade
CA-OTO	Turnover: Sale, maintenance and repair of motor vehicles and motorcycles
CA-GRO	Turnover: Wholesale trade and commission trade
CA-HR	Turnover: Hotels and restaurants
CA-TT	Turnover: Land transport
CA-TA	Turnover: Air transport
CA-TS	Turnover: Auxiliary services to transport
CA-PTT	Turnover: Post office and telecommunications network
CA-INF	Turnover: Computing activity
CA-SE	Turnover: Services for enterprises
CA-DMET1	Turnover: Basic metals and fabricated metal products, domestic market
CA-XMET1	Turnover: Basic metals and fabricated metal products, non-domestic market
SAL	Wages and salaries: Total industry excluding construction
SAL-BTP	Wages and salaries: Building and Civil engineering
CSU-m	Unit labour costs: Manufacturing
RSU-M	Labour price index: Manufacturing
RMO-M	Average earnings per employee: Manufacturing
GMO-M	Average hourly earnings of wage earners: Manufacturing
SAL-I	Gross wages and salaries: Intermediate Goods Industry
SAL-MET1	Gross wages and salaries: Basic metals and fabricated metal products
SAL-MET2	Gross wages and salaries: Fabricated metal products, except machinery
EMPSAL	Employment: civilian domestic employees
NSAL-BTP	Number of employees : Civil engineering and building
NSAL	Number of employees: Total industry excluding construction
RESIDE	Employees resident in Luxembourg
TRPR-BTP	Hours worked : Civil engineering and building
TRAPRES	Hours worked: Total industry excluding construction
CHILO	Number of unemployed (thousand)
OENS	Registered vacancies
L-I	Employment: Intermediate Goods Industry
L-MET1	Employment: Basic metals and fabricated metal products
L-MET2	Employment: Fabricated metal products, except machinery
HW-I	Hours worked: Intermediate Goods Industry
HW-MET1	Hours worked: Basic metals and fabricated metal products
HW-MET2	Hours worked: Fabricated metal products, except machinery
UNEMP	Unemployment rate

Table 8: Dataset *(continued)*

COM	New orders: Total industry excluding construction
$\mathrm{NCOM}_X I$	-: Non-domestic market, Intermediate Goods Industry
NCOM_I	-: Total, Intermediate Goods Industry
NCOM-XMET1	-: Non-domestic market, Basic metals and fabricated metal products
NCOM-MET1	-: Total, Basic metals and fabricated metal products
NCOM-XMET2	-: Non-domestic market, Fabricated metal products, except machinery
NCOM-MET2	-: Total, Fabricated metal products, except machinery
PER-TNB	Number of building permits issued: Total
PER-TNL	Number of building permits issued: Residential
PER-INB	Number of building permits issued: Individual housing
PER-ANB	Number of building permits issued: Collective housing
PER-ANL	Number of building permits issued: Collective housing, number of flat
PER-IVB	Building permits issued: Volume, Individual housing
PER-AV	Building permits issued: Volume, collective housing
IMAC	Car registrations: Commercial cars
IMATP	Car registrations: Private cars
OCCASO	Imported cars
LUXX	Luxembourg Stock Price Index - LUXX
EXR	Exchange rate: Euro / US Dollar
STI	Three-month Euribor rate
SOTOBI	Aggregated balance sheet of the Luxembourg banks
X	Merchandise trade: Total exports
M	Merchandise trade: Total imports
X-OUT	Merchandise trade: Exports to non-EU countries(EU-25)
X-IN	Merchandise imports, CIF, From non-EU countries(EU-25)

Table 9: Dataset details

Series	Type of treatment	Commonality	Classification*
GDP	(1-L)log	0.59	reference series
NICP	(1-L)log	0.546	R
OIL	(1-L)log	0.44	A
$\text{PER}_T NB$	(1-L)log	0.696	A
$\text{PER}_T NL$	(1-L)log	0.636	A
$\text{PER}_I NB$	(1-L)log	0.671	R
$\text{PER}_A NB$	(1-L)log	0.635	R
$\text{PER}_A NL$	(1-L)log	0.517	A
$\text{PER}_I VB$	(1-L)log	0.659	R
$\text{PER}_A V$	(1-L)log	0.492	A
IMAC	(1-L)log	0.554	R
IMATP	(1-L)log	0.538	C
SAL	(1-L)log	0.737	R
EMPSAL	(1-L)log	0.762	R
$\text{NSAL}_B TP$	(1-L)log	0.649	R
NSAL	(1-L)log	0.479	R
RESIDE	(1-L)log	0.663	R
$\text{TRPR}_B TP$	(1-L)log	0.526	R
TRAPRES	(1-L)log	0.613	R
OCCASO	(1-L)log	0.533	A
COM	(1-L)log	0.663	A
$\text{PPI}_D O$	(1-L)log	0.663	A
IP	(1-L)log	0.89	R
PPI	(1-L)log	0.89	R
PPI_I	(1-L)log	0.89	R
PPI_K	(1-L)log	0.89	R
PPI_C	(1-L)log	0.89	R
CA_B	(1-L)log	0.468	A
$\text{CA}_T P$	(1-L)log	0.517	R
CA_I	(1-L)log	0.579	R
$\text{CA}_D ET$	(1-L)log	0.471	R

*R, A and C for respectively lagged, leading and coincident series.

Table 10: Dataset details *(continued)*

Series	Type of treatment	Commonality	Classification
CHILO	(1-L)log	0.39	A
OENS	(1-L)log	0.339	R
SAL_BTP	(1-L)log	0.597	R
PJO_B	(1-L)log	0.519	R
PJO_TP	(1-L)log	0.587	A
PJO	(1-L)log	0.876	R
PJO_I	(1-L)log	0.824	R
PPI_BTP	(1-L)log	0.824	R
CET	(1-L)	0.63	C
STO	(1-L)	0.485	R
CTX	(1-L)	0.622	C
PERSP	(1-L)	0.425	R
TPPA	(1-L)	0.515	R
PPI_X	(1-L)log	0.515	R
YEMP_MA	(1-L)log	0.902	R
YEMP	(1-L)log	0.663	R
YHR	(1-L)log	0.846	R
YHRL	(1-L)log	0.834	R
PPI_IX	(1-L)log	0.834	R
LUXX	(1-L)log	0.46	A
CA_OTO	(1-L)log	0.6	R
CA_GRO	(1-L)log	0.653	R
CA_HR	(1-L)log	0.633	R
CA_TT	(1-L)log	0.399	R
CA_TA	(1-L)log	0.341	R
CA_TS	(1-L)log	0.447	R
CA_PTT	(1-L)log	0.361	A
CA_INF	(1-L)log	0.445	R
CA_SE	(1-L)log	0.423	R
CSU_m	(1-L)log	0.725	R
RSU_M	(1-L)log	0.81	R
RMO_M	(1-L)log	0.706	R

Table 11: Dataset details *(continued)*

Series	Type of treatment	Commonality	Classification
$L_M ET1$	(1-L)log	0.443	R
$L_M ET2$	(1-L)log	0.381	R
$HW_M ET1$	(1-L)log	0.606	R
$HW_M ET2$	(1-L)log	0.396	C
$NCOM_X MET1$	(1-L)log	0.578	C
$NCOM_X MET2$	(1-L)log	0.487	R
$NCOM_M ET1$	(1-L)log	0.545	C
$NCOM_M ET2$	(1-L)log	0.491	A
$CA_D MET1$	(1-L)log	0.38	R
$CA_X MET1$	(1-L)log	0.594	R
UNEMP	(1-L)log	0.422	A
$SAL_M ET1$	(1-L)log	0.52	R
$SAL_M ET2$	(1-L)log	0.481	R
EXR	(1-L)log	0.475	C
X	(1-L)log	0.572	R
M	(1-L)log	0.514	R
$X_O UT$	(1-L)log	0.426	R
$X_I N$	(1-L)log	0.441	R
PERSPX	(1-L)	0.59	C
PERSPE	(1-L)	0.436	R
ACPAS	(1-L)	0.428	R
CCOM	(1-L)	0.4	C
EXPEM	(1-L)	0.447	C
EXPX	(1-L)	0.463	C
SOTOBI	(1-L)log	0.403	R
STI	(1-L)	0.583	R
GMO_M	(1-L)log	0.634	R
PJO_M	(1-L)log	0.88	R
PJO_K	(1-L)log	0.611	R
PJO_J	(1-L)log	0.372	A
L_I	(1-L)log	0.38	R
HW_I	(1-L)log	0.487	C
$NCOM_X I$	(1-L)log	0.579	C
$NCOM_I$	(1-L)log	0.476	R
SAL_I	(1-L)log	0.524	R
IP_I	(1-L)log	0.703	C